*Proc. of the International Conference on Electrical, Computer and Energy Technologies (ICECET)*
*9-10 December 2021, Cape Town-South Africa*

# Rice Texture Analysis Using GLCM Features

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2021 International Conference on Electrical, Computer and Energy Technologies (ICECET) | 978-1-6654-4231-2/21/$31.00 ©2021 IEEE | DOI: 10.1109/ICECET52533.2021.9698594

***Abstract*— Texture analysis plays an important role in digital image processing. Texture can be considered as a grouping of similarities in an image, because the computer does not have a sense of sight then the computer only knows the pattern of a digital image from its texture characteristics. Texture characteristics of an image can be obtained through the feature extraction process. In this study, we carried out a texture analysis process using the GLCM (Gray level co-occurrence matrices) method on rice images where the rice images that we carried out in groups and not per grain. The results of this study are used to classify the texture of the image of good and damaged rice based on the features of contrast, correlation, energy and homogeneity values with angles of $0^0$, $45^0$, $90^0$ and $135^0$, where the GLCM method applied is able to analyze the texture characteristics of the rice image.**

***Keywords*— rice, digital image, texture analysis, GLCM***

## I. Introduction

Rice is the main staple food which is the most important commodity in everyday human life in Indonesia. The quality of rice can be affected by the texture of the rice by using image processing. In image processing, one way to get information from an image is through the features contained in the image. Each image is often described through a set of features that make up a high-dimensional space [1] or an application that involves an automatic features extraction from an image [2].

Texture is an important characteristic for the analysis of many types of images because it provides a rich source of information about the image or the main terms used to define the object or concept of an image [3]. An image is said to have texture if the image pattern occurs repeatedly in all areas of the image. The area of texture analysis consists of texture segmentation, texture synthesis, texture shape and texture classification [4]. The methods in texture classification are categorized as follows statistical [5], [6], [7], structural [8], [9], [10] , model based [11], [12], [13] and transform based [14], [15], [16].

In this article, we conduct a study on rice texture analysis using the gray level co-occurrence matrix (GLCM) method which is included in the statistical category where the rice images that we carried out in groups and not per grain.

## II. Experimental Detail

### A. Proposed System

The design of the proposed system of this study using the GLCM (Gray level co-occurrence matrices) method as shown in Fig.1.

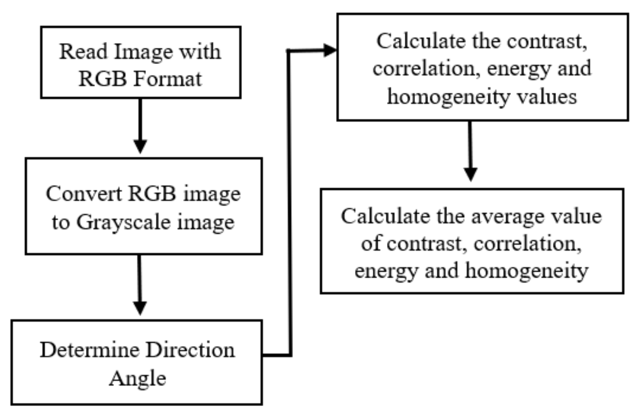


Fig.1. Proposed System

### B. Image Input and Image Conversion

At this stage, the image used is an image of rice in RGB (Red, Green, Blue) format [17]. RGB is a standard color space based on color frequency acquisition result by electronic sensors that are encoded in 8 bits for each color. Next, the image conversion is carried out from an RGB format image to a grayscale image with the rgb2gray function in matlab.

### C. Angle Direction

The size of the co-occurrence matrix is very dependent on the minimum and maximum values of the pixels in the analyzed texture area, while the value of each matrix element is the number of frequencies the value of two pixels occurs which are

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neighboring. The reading of the value of two neighboring pixels will depend on the definition of the distance d = {dy, dx} between the two pixels and angle θ as the direction of neighboring, namely horizontal, vertical and diagonal. . The mathematical equation for the co-occurrence matrix for size of G x G from an N x M image area as shown in (1).

$$CM_{d,\theta}(i,j) = \left|\{(n,m),(n+d_y,\ m+\ d_x));\ I(n,m) = i, l(n+\ d_y, m+\ d_x) = j\}\right| \quad (1)$$

Where:
$(n,m),(n+d_{y,}\ m+\ d_x)\ \in NxM$
i= pixel value at position (n,m)
j = pixel value at position $(n+\ d_y, m+\ d_x)$
G = the difference between the maximum and minimum values of pixels in the analyzed image area

Fig. 2, shows an image of the direction of the neighboring pixels for the calculation of the co-occurance matrix with the position of the neighboring pixels p(n, m) according to the angle directions of $0^0$, $45^0$, $90^0$ and $135^0$. The neighboring pixels for direction $0^0$ is p(n, m+d) , $45^0$ is p(n-d, m+d), $90^0$ is p(n-d, m) dan $135^0$ is p(n-d, m-d).

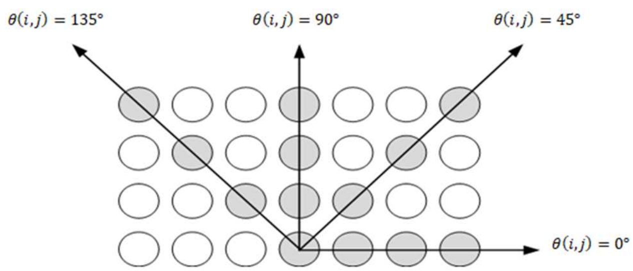



Fig. 2. Angle of Neighboring pixels

*D. Contrast, Correlation, Energy and Homogeinety*

Contrast is the variation of local intensity values in the co-occurrence matrix. If neighboring pixels have similar intensity values or adjacent then the texture contrast is very low. High contrast values indicate textures with high intensity variations, for low contrast values indicate smooth or soft textures as shown in (2).

$$Contrast = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\ (i-j)^2\ P\ (i,j) \quad (2)$$

Correlation is a measure of the linear connectivity of the gray level of one pixel relative to other pixels. The correlation is expected to be high if the gray level of the pair of highly correlated pixels as shown in (3).

$$Correlation = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\ \frac{(i-\mu_x)(j-\mu_y)\ P(i,j)}{\sigma_x\sigma_y} \quad (3)$$

Energy is a measure of local homogeneity and opposite of entropy. This feature is used for the level of texture uniformity. The higher energy value, the higher level of texture homogeneity. The energy value is in the range of [0,1], where 1 represents a homogeneous area as shown in (4).

$$Energy = \sum_{j=0}^{G-1}\sum_{i=0}^{G-1}\left(P(i,j)\right)^2 \quad (4)$$

Homogeneity is a measure of the proximity of each element of the co-occurrence matrix. The level of texture homogeneity is very high when the value of the co-occurance matrix is concentrated along the diagonal matrix and has a range of values [0,1]. For the homogeneity value equal to 1 indicates that the texture has an ideal repetition structure, if the value is low, it indicates that the texture element has a high variation and spread evenly in the texture area as shown in (5).

$$Homogeneity = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\ \frac{P(i,j)}{1+(i-j)^2} \quad (5)$$

*E. GLCM Algorithm*

1) Read Image.
2) Display the original image (RGB format).
3) Convert RGB image to Grayscale Image and display the grayscale image.
4) Determine direction angle for $0^0$ = {0, d}, $45^0$ = {-d,d}, $90^0$ = {-d, 0}, $135^0$ = {-d,-d}.
5) Calculate the contrast, correlation, energy and homogeneity values.
6) Calculate the average value of contrast, correlation, energy and homogeneity.

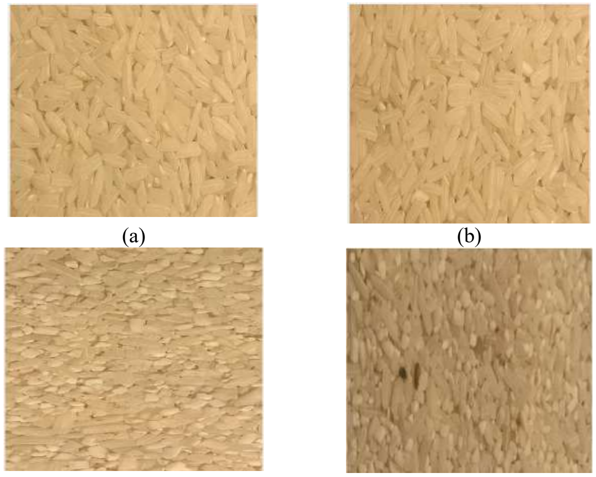
*F. Object Classification*

Classification of rice grains based on the size of the rice consisting of Long Slender (LS), Short Slender (SS), Medium Slender (MS), Long Bold (LB) and Short Bold (SB) [18]. In this study, the rice we used was rice with a length of 6 mm to above 6 mm.

## III. RESULT AND DISCUSSION

The rice image used in this study, we classify into 2 parts namely the image of good rice is rice that whole, clean or rice with a minimum size of more than 50% of its original size. while the image of damaged rice is rice with a size of less than 50% of its original size, brown rice, black rice or a combination of good and damaged rice in the rice group.

Rice image used in this study is shown in Fig.3, where the rice image used is done not per grain but in groups captured through a digital camera with RGB format, figure 3(a), (b) are a good rice image in the form of a collection of whole rice, clean or rice with a minimum size of more than 50% of the original size while figure 3(c), (d) are an image of damaged rice in the form of rice with a size of less than 50% of its original size, brown rice, black rice or a combination of good rice and damaged rice in that group of rice.

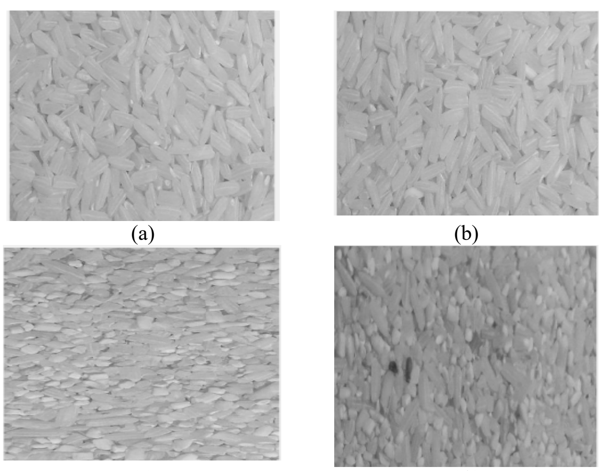


(a) (b)

(c) (d)

Fig. 3. Image of good and damaged rice in RGB format

The image of good and damaged rice in Grayscale format are shown in Fig. 4, where images 4 (a) and (b) grayscale images from the results of processing images 3 (a) and (b), while images 4 (c) and (d) grayscale images from the results of image processing 3 (c) and (d).



(a) (b)

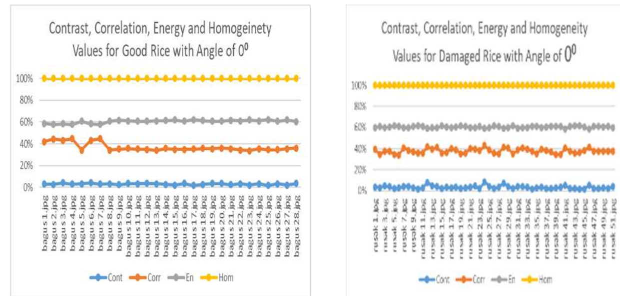
(c) (d )

Fig. 4. Image of good and damaged rice in Grayscale format

The rice testing in this study were 79 rice images consisting of 28 good rice images and 51 damaged rice images. For good and damaged rice, we group them in an area as shown in Figures 3 (a), (b), (c) and (d), while the features of the Gray Level Co-occurrence matrix (GLCM) used are contrast, correlation, energy, homogeneity with angles of $0^0$, $45^0$, $90^0$ and $135^0$ and pixel distance was 1.

The results of the GLCM process for good and damaged rice with an angle of $0^0$ are shown in Fig. 5. In Fig. 5(a) for the average contrast value of 0.07198 then it shows a smooth texture, average the correlation value of 0.82328 then it shows a measure of the connection between the high gray level pixels, average the energy value of 0.58149 then it shows that the level of homogeneous area of the texture is low and average the homogeneity value of 0.96422 indicates that the texture has almost ideal repeating structure.

In Fig. 5(b) for average the contrast value of 0.08194 then it shows a smooth texture, average the correlation value of 0.83634 then it shows a measure of the connection between the high gray level pixels, average the energy value of 0.55371 then it shows that the level of homogeneous area of the texture is low and average the homogeneity value of 0.95949 indicates that the texture has almost ideal repeating structure.

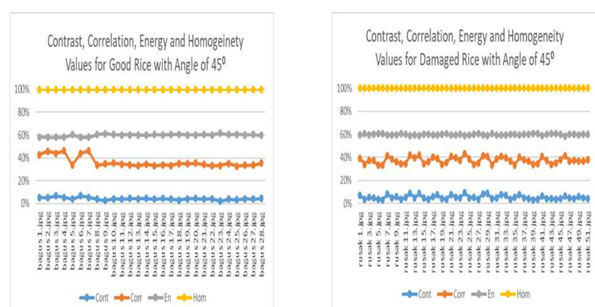



(a) (b)

Fig.5. GLCM process with angle of $0^0$ on good and damaged rice

The results of the GLCM process for good and damaged rice with an angle of $45^0$ are shown in Fig. 6. In Fig. 6(a) for the average contrast value of 0.101855 then it shows a smooth texture, average the correlation value of 0.75943 then it shows a measure of the connection between the high gray level pixels, average the energy value of 0.5608 then it shows that the level of homogeneous area of the texture is low and average the homogeneity value of 0.94981 indicates that the texture has almost ideal repeating structure.

In Fig. 6(b) for average the contrast value of 0.124182 then it shows a smooth texture, average the correlation value of 0.750879 then it shows a measure of the connection between the high gray level pixels, average the energy value of 0.525463 then it shows that the level of homogeneous area of the texture is low and average the homogeneity value of 0.939793 indicates that the texture has almost ideal repeating structure.

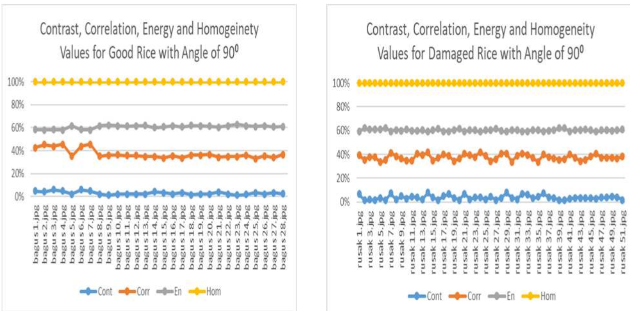



(a) (b)

Fig.6. GLCM process with angle of $45^0$ on good and damaged rice

The results of the GLCM process for good and damaged rice with an angle of $90^0$ are shown in Fig. 7. In Fig. 7(a) for the average contrast value of 0.071298 then it shows a smooth texture, average the correlation value of 0.839288 then it shows a measure of the connection between the high gray level pixels, average the energy value of 0.583538 then it shows that the level of homogeneous area of the texture is low and average the homogeneity value of 0.96458 indicates that the texture has almost ideal repeating structure.

In Fig. 7(b) for average the contrast value of 0.090951 then it shows a smooth texture, average the correlation value of 0.816793 then it shows a measure of the connection between the high gray level pixels, average the energy value of 0.548168 then it shows that the level of homogeneous area of the texture is low and average the homogeneity value of 0.955486 indicates that the texture has almost ideal repeating structure.

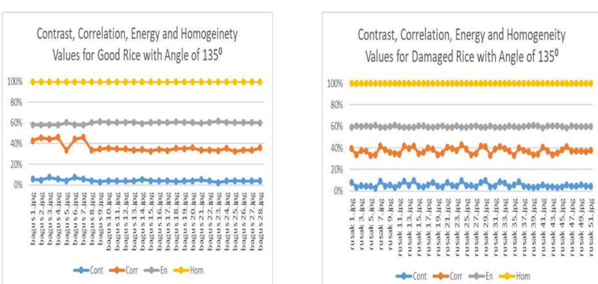



(a) (b)

Fig7. GLCM process with angle of $90^0$ on good and damaged rice

The results of the GLCM process for good and damaged rice with an angle of $135^0$ are shown in Fig. 8. In Fig. 8(a) for the average contrast value of 0.10177 then it shows a smooth texture, average the correlation value of 0.75991 then it shows a measure of the connection between the high gray level pixels, average the energy value of 0.56084 then it shows that the level of homogeneous area of the texture is low and average the homogeneity value of 0.94978 indicates that the texture has almost ideal repeating structure.

In Fig. 8(b) for average the contrast value of 0.12622 then it shows a smooth texture, average the correlation value of 0.74747 then it shows a measure of the connection between the high gray level pixels, average the energy value of 0.52468 then it shows that the level of homogeneous area of the texture is low and average the homogeneity value of 0.93904 indicates that the texture has almost ideal repeating structure.




(a) (b)

Fig.8. GLCM process with angle of 1350 on good and damaged rice

The results of the analysis using the GLCM method show that the rice we studied have the following characteristics a. texture has a smooth texture based on contrast, b. texture has a high level of gray level connectivity between pixels based on correlation, c. texture has a low level of homogeneous area based on energy and d. texture has almost ideal repeating structure based on homogeneity.

## IV. CONCLUSION

The methods and algorithms used in this study to obtain the features of the texture of the rice based on 4 features namely contrast, correlation, energy and homogeneity are very effective. Future work, we will continue our current research by focusing on the identification of good and damaged rice using the convolutional neural network (CNN) method.

## ACKNOWLEDGMENT

We would like to thank the Ministry of Research and Technology / BRIN for the financial assistance and LP2S UMI which have helped facilitate this research activity.

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